MODELING OF LITHIUM-ION BATTERY AND STATE OF CHARGE ESTIMATION USING MATLAB/SIMULINK

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DEDICATION

This thesis is dedicated to my father, who taught me that the best kind of knowledge to have is that which is learned for its own sake. It is also dedicated to my mother, who taught me that even the largest task can be accomplished if it is done one step at a time.

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ABSTRACT

Due to a lack of sustainable energy sources and the effects of climate change, the development of electric vehicles (EVs) have accelerated during the past years. One of the major technologies used in EVs, the battery, likewise contributes to the growth of EVs being constrained. Due to its high energy density, extended lifespan, high efficiency, quick charging capability, and minimal self-discharge, lithium ferro phosphate (LiFePO4) is among the lithium-ion batteries that is widely utilised. The state of charge (SOC) assessment of the battery is a crucial characteristic that must be carefully taken into account for battery management systems (BMS). To monitor how the battery pack is being charged and discharged, optimise performance, and increase battery life, it is essential that the SOC estimation be accurate. The SOC calculation gets exceedingly complicated because the battery stores energy in a chemical state that cannot be immediately accessed. Additionally, there are several uncertainties and disturbances that make judging the accuracy of a SOC estimation difficult. This project's objectives concentrate on creating a LiFePO4 battery model utilising an Equivalent Circuit Model (ECM) to forecast SOC using the Unscented Kalman Filter (UKF) technique. Two different types of battery ECM modules with two RC pairs and three RC pairs were studied to compare the model's accuracy. Using the dynamic behaviours of a LiFePO4 battery from an experimental data, the battery ECM parameters were calculated using the MATLAB Parameter Estimation Tool. Constant Discharge Test (CDT), Pulse Discharge Test (PDT), and Random Charge and Discharge Test (RCDT) have all been used in experiments to examine the dynamic properties of the LiFePO4 battery. Battery ECMs with two RC pair and three RC pairs were used to achieve the SOC estimation using the UKF block algorithm in MATLAB. Then, using error analysis tools including Mean Square Error (MSE), Mean Absolute Error (MAE) and Root Mean Square Error (RMSE), the accuracy of the battery ECMs was analysed. The most precise battery ECM was chosen to be used in the UKF method to predict the SOC of a LiFePO4 battery based on the findings of the error analysis. After that, the simulation's result is verified by comparison to the actual SOC using the Coulomb Counting technique. Then, using error analysis like MAE, MSE, and RMSE, the performance of a UKF algorithm was compared to an Extended Kalman Filter (EKF). The most accurate method for estimating value of SOC is chosen depend on the results of the error analysis.

ABSTRAK

Disebabkan kekurangan sumber tenaga mampan dan kesan perubahan iklim, pembangunan kenderaan elektrik (EV) telah dipercepatkan sejak beberapa tahun lalu. Salah satu teknologi utama yang digunakan dalam EV, bateri, juga menyumbang kepada pertumbuhan EV yang dikekang. Disebabkan oleh ketumpatan tenaga yang tinggi, jangka hayat yang dilanjutkan, kecekapan tinggi, keupayaan pengecasan pantas dan pelepasan diri yang minimum, litium ferro fosfat (LiFePO4) adalah antara bateri litium-ion yang digunakan secara meluas. Penilaian keadaan pengecasan (SOC) bagi bateri ialah ciri penting yang mesti diambil kira dengan teliti untuk sistem pengurusan bateri (BMS). Untuk memantau cara pek bateri dicas dan dinyahcas, mengoptimumkan prestasi dan meningkatkan hayat bateri, adalah penting bahawa anggaran SOC adalah tepat. Pengiraan SOC menjadi sangat rumit kerana bateri menyimpan tenaga dalam keadaan kimia yang tidak boleh diakses dengan segera. Selain itu, terdapat beberapa ketidakpastian dan gangguan yang menyukarkan menilai ketepatan anggaran SOC. Objektif projek ini menumpukan pada mencipta model bateri LiFePO4 menggunakan Model Litar Setara (ECM) untuk meramalkan SOC menggunakan teknik Penapis Kalman Tidak Berbau (UKF). Dua jenis modul ECM bateri dengan dua pasangan RC dan tiga pasangan RC telah dikaji untuk membandingkan ketepatan model. Menggunakan tingkah laku dinamik bateri LiFePO4 daripada data eksperimen, parameter ECM bateri dikira menggunakan Alat Anggaran Parameter MATLAB. Ujian Nyahcas Malar (CDT), Ujian Nyahcas Nadi (PDT), dan Ujian Caj dan Nyahcas Rawak (RCDT) mempunyai semuanya telah digunakan dalam eksperimen untuk mengkaji sifat dinamik bateri LiFePO4. ECM bateri dengan dua pasangan RC dan tiga pasangan RC telah digunakan untuk mencapai anggaran SOC menggunakan algoritma blok UKF dalam MATLAB. Kemudian, menggunakan alat analisis ralat termasuk Ralat Mean Square (MSE), Ralat Min Mutlak (MAE) dan Ralat Purata Purata Akar (RMSE), ketepatan ECM bateri telah dianalisis. ECM bateri yang paling tepat telah dipilih untuk digunakan dalam Kaedah UKF untuk meramalkan SOC bateri LiFePO4 berdasarkan penemuan analisis ralat. Selepas itu, keputusan simulasi disahkan dengan perbandingan dengan SOC sebenar menggunakan teknik Coulomb Counting. Kemudian, menggunakan analisis ralat seperti MAE, MSE dan RMSE, prestasi algoritma UKF dibandingkan dengan Penapis Kalman Lanjutan (EKF). Kaedah yang paling tepat untuk menganggar nilai SOC dipilih bergantung kepada keputusan analisis ralat.

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LIST OF ABBREVIATIONS

BMS	-	Battery Management System
CC	-	Coulomb Counting
CDT	-	Constant Discharge Test
CO	-	Carbon Monoxide
CO2	-	Carbon Dioxide
DAQ	-	Data Acquisition Device
ECM	-	Equivalent Circuit Model
EKF	-	Extended Kalman Filter
EV	-	Electric Vehicle
GHG	-	Green House Gas
IEA	-	International Energy Agency
Li-Io	-	Lithium Ion
LiFePO4	-	Lithium Ferro Phosphate
MAE	-	Mean Absolute Error
MSE	-	Mean Square Error
OCV	-	Open Circuit Voltage
PDT	-	Pulse Discharge Test
PF	-	Particle Filter
PV	-	Photovoltaic Solar
RC	-	Resistor-Capacitor
RCDT	-	Random Charge and Discharge Test
RMSE	-	Root Mean Square Error
SOC	-	State of Charge
SOH	-	State of Health
SOP	-	State of Power
UKF	-	Unscented Kalman Filter
UTM	-	Universiti Teknologi Malaysia

LIST OF SYMBOLS

A	-	Battery capacity
α_U	-	Usable capacity
C_1	-	Capacitance in first RC parallel network
C_2	-	Capacitance in second RC parallel network
C_3	-	Capacitance in third RC parallel network
R_s	-	Series resistance
R_1	-	Resistance in first RC parallel network
R_2	-	Resistance in second RC parallel network
R_3	-	Resistance in third RC parallel network
t	-	Battery runtime
t_E	-	Ending time of relaxation
t_R	-	Ending time of loaded condition
t_S	-	Starting time of loaded condition
V_{k1}	-	Voltage across first RC parallel network
V_{k2}	-	Voltage across second RC parallel network
V_{k3}	-	Voltage across third RC parallel network
V_t	-	Battery voltage
γ	-	State of charge
γ_0	-	Initial SOC of battery
vk	-	The sensor noise
wk	-	Process noise or disturbance to the system
xk	-	System state vector at time index k
yk	-	Defined as output equation

LIST OF APPENDICES

CHAPTER 1

INTRODUCTION

1.1 Research Background

Energy storage is required for solar energy harvesting as well as electric vehicles to work properly. Lead acid batteries are the most often utilised in photovoltaic solar (PV) systems, according to [1]. However, a recent study found that lithium-ion batteries had a significant edge over lead acid batteries in terms of energy efficiency and economic.

Lithium-ion batteries have also been widely employed in EV applications because to its extended cycle lifespan, great energy efficiency and density, and relatively low environmental impact [2]. Because lithium-ion batteries were commonly using in electric vehicles and solar photovoltaic systems, the battery management systems (BMS) is critical for ensuring safe battery operation through monitoring a charge and discharge process due to the state of charge (SOC), state of health (SOH), state of power (SOP), and state of energy [2].

Estimating battery status is a crucial BMS function. The two crucial states that need to be calculated are the state of charge (SoC) and the state of health (SoH). In this situation, SoH reveals the battery's performance deterioration while SoC provides information on the battery's remaining capacity. The EV driver has to know these battery states in order to gauge the battery pack's current condition. Due to the fact that states cannot be directly assessed, it is regarded as the most difficult assignment for a BMS. Additionally, the estimation should be performed without impairing the EV's functionality [2].

Generally, SoC is typically referred to as the battery's remaining stored energy. Also, the SoC estimate serves as the "fuel gauge" for EV applications, which is essential for estimating the driving range. To avoid EVs running out of juice while driving, a precise SoC estimate is necessary [3]. Additionally, SoC is crucial for improving battery efficiency by carefully regulating the charge - discharge operations, particularly in hybrids energy storage systems.

However, calculating SoC is a challenging procedure that depends on a number of variables, including temperature, useable capacity, and series resistance [3]. There have been a number of strategies for SoC estimation that may be divided into three groups:

(i) Direct measurement techniques.
(ii) State-space for model-based techniques.
(iii) Black-box for model-based techniques.

1.2 Battery Management Systems

The major goal of BMS installation is to continually monitor and manage the lithium-ion battery's varied states during its operating duration [4]. Battery characteristics such as operational current and voltage, SoC, ambient temperature, SoH, battery ageing, and internal impedance must be observed and estimated by the BMS [4]. Figure 1.1 shown an example of a generic BMS.

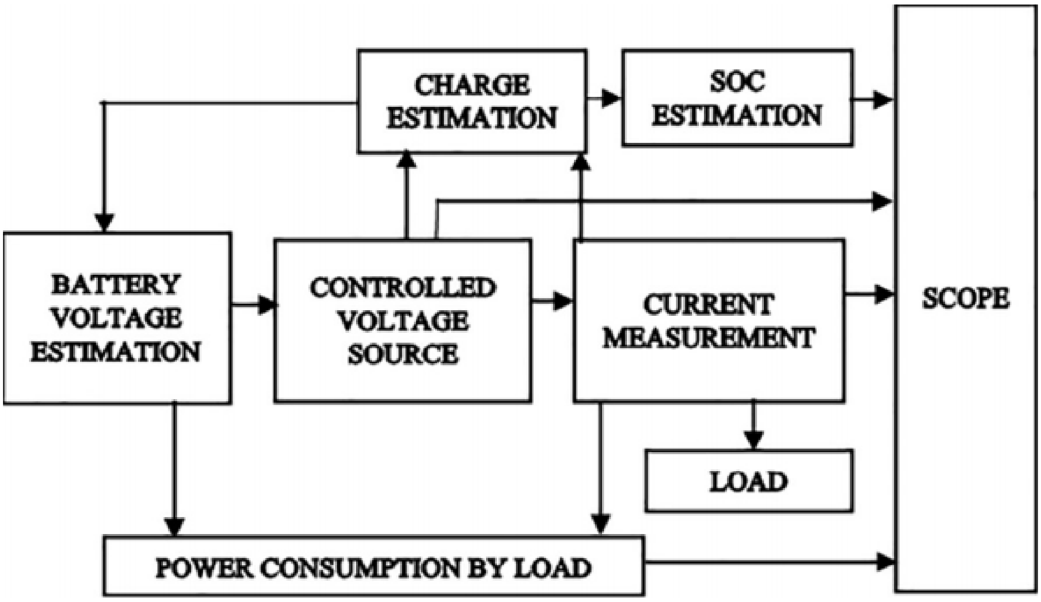

Figure 1.1 Block Diagram of General BMS [4]

1.2.1 Modelling of Battery

The BMS uses a battery model to represent the real battery in an indirect way. The surfaces temperature, terminal currents, and voltages of the battery are all sensed using various sensors. The battery model will then be used to estimate battery states such like SoC, SoH, and SoP using all of the data. In fact, for the batteries model to work correctly, the parameters must always be pre-determined [5].

Numerous battery models have already been investigated. They are usually divided into three types: equivalent circuit modeling, empirical model, and electrochemical model. Because it is based on physical's and chemical reactions in the battery, the electrochemical model is thought to be the most accurate. However, due to the model's complexity, that is not the best model for implementation in the BMS. The empirical model is a simplified variant of the electrochemical model, often known as a mathematical model. The complexity is decreased, but the batteries model accuracy is dropped by over 20%. To represent the battery properties, an equivalent circuit model (ECM) is made up of a series resistor and a resistor-capacitor (RC) pair.

It has a high degree of precision and is less difficult to implement in the BMS according to [5].

1.2.2 State of Charge Estimation

The SOC for a battery will not be directly measure because it represents the electricals energy stored in a chemical state. As a result, SOC must be calculated in the BMS using the battery model and measured battery data including surface temperature, terminal current, and voltage. The SOC's performance must be accurate, dependable, and stable. Many approaches for estimating SOC have been investigated. They may be divided into three categories: conventional methods, adaptive methods, and learning algorithms. The open circuit voltage (OCV) approach is a conventional method that has good accuracy but cannot be used in an online BMS application. The Kalman Family Filters as well as the Particle Filter (PF) are examples for adaptive filters according to [6].

1.3 Problem statement

The lithium ferro phosphate (LiFePO4) batteries are widely used in electric vehicles (EVs) as an energy storage component since it can provide a larger energy capacity over a longer length of time and is ecologically friendly. As a result, a BMS that incorporates a battery model becomes essential for serving like a guide for the system styler to predict the battery's dynamic behaviours. The BMS will accurately estimate the battery's SOC and then optimise the battery's performance by controlling the charging or discharging process of the battery by using an accurate batteries ECM and an accurate estimation state algorithm.

However, due to numerous uncertainties and noises, designing the SOC estimation of a battery accurately is exceedingly difficult. The precision of the SOC predictions would decrease as a result of the effects of the ambient air temperature, sensor measurement stability, battery temperature and fluctuations in terminal current and voltage. Consequently, in order to account for all the noises as well as uncertainties with a more precise predictions of the battery SOC, more research on a battery SOC estimate is therefore very essential.

1.4 Research Objectives

The objectives of the research are:

(a) To develop a model of battery by using the Equivalent Circuit Model (ECM) and compute the parameters of the battery model by using experimental data on the properties of the LiFePO4 battery.

(b) To implement the battery ECMs for estimation SOC by using the Unscented Kalman Filter (UKF) algorithm, then will determine the optimal design of battery ECM.

(c) To analyse the performances of the UKF algorithm SOC estimation by comparing a simulation results with the real SOC by Coulomb Counting (CC) of a LiFePO4 battery and with the Extended Kalman Filter (EKF) algorithm that has been Procedure from a previous researches.

1.5 Research Scopes

This research can focus on the following scopes in order to fulfil the above-mentioned objectives:

(a) The LiFePO4 battery is selected due to its environmentally friendly and fast charging performance.

(b) Battery ECM's is considered as a cell level only, making it possible to ignore issues with many cells such cell imbalance as well as individual cell voltage monitoring.

(c) Two levels of RC pairs component will use in equivalent circuit model for a battery modelling.

(d) UKF method is chose to performing Soc estimate due to its robustness and accuracy.

(e) The performances for UKF algorithm will analyze by comparing to the real SOC by CC and EKF technique.

1.6 Research Outline

In chapter 2, several literatures and earlier works are researched and analysed in order to continue with this report. The battery modelling plus SOC estimation techniques are the two primary sections of the literature review. To find the optimum battery model to deploy, various battery models are evaluated and compared. Following that, numerous SOC estimate approaches are investigated in order to compare their performance and complexity. As a result, the SoC estimate approach is chosen because of its high accuracy and simplicity.

In chapter 3, the approach for achieving the research aims is proposed. The process begins with the LiFePO4 experimental work. The Pulse Discharge Test (PDT), Random Charge and Discharge Test (RCDT), and Constant Discharge Test (CDT) tests are used to assess the dynamic properties of the battery, allowing the battery parameters of the model to be calculated. Because the SOC of a LiFePO4 batteries cannot be determined directly, the SOC is calculated using the Coulomb Counting technique based on observed current. This SOC is regarded as the LiFePO4 battery's true SOC. After that, the SOC will be calculated using the Unscented Kalman Filter (UKF). The UKF's performance will be assessed by comparing the error analysis to that of the real SOC and EKF technique. As a result, the optimum strategy for estimating SOC may be given.

The findings have been discussed in chapter 4. The PDT, CDT, and RCDT are presented. As a result, the LiFePO4 battery's dynamic characteristics may be shown. Then, using the Coulomb Counting technique, the actual SOC LiFePO4 battery was identified. This chapter also covers the findings from the previous researcher's study, which used the EKF technique to estimate SOC. The outcomes of the estimate of the battery's ECM RC parameters using the MATLAB Parameter Estimation Tool are also shown. After that, the effectiveness of two types battery ECMs is presented and analysed using MATLAB's UKF block technique. In order to describe the final outcome, the performances for an UKF algorithm is compared to the performances of an EKF method.

Finally, chapter 5 includes conclusion of the project and it discuss the future work that needs to be conducted for future. This involves using new estimation algorithm such like Dual UKF (DUKF) and Dual EKF (DUKF) to estimate online SOC for a LiFePO4 battery because these amended algorithms have a better accuracy and performance in state estimation.

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